

LA-UR-21-20971

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Title: Subtask 3.1: Sequential Design of Experiments

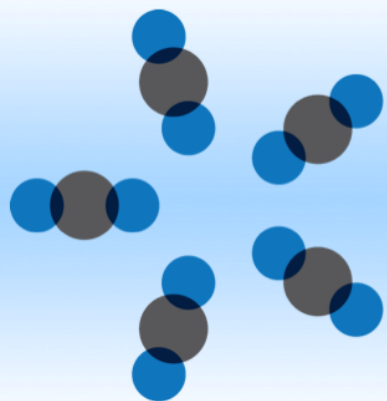
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CCSI²

Carbon Capture Simulation for Industry Impact

Subtask 3.1: Sequential Design of Experiments

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January 2021

Subtask Team:

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Charles Tong (LLNL)



Why Design of Experiments in CCSI²?

- Data in Carbon Capture applications are expensive
 - Time at test facilities difficult to obtain and requires waiting
- } Want to make most of data that we are able to get
- Sequential Design of Experiments:
 - Allows us to be strategic about choosing what data are most beneficial
 - Tailor data collection to the specific goals of each experiment (or stage of experiment)
 - Leverage what we already know to take maximum advantage of new data
 - SDoE module in FOQUS provides tools for experimenters to
 - Incorporate what is already known about a process
 - Quickly generate a designed experiment to match their objectives



EY20 Highlights

- New release of FOQUS SDoE module with new capabilities

- **Space-Filling design**

- Uniform Space-Filling (USF)
- Non-Uniform Space-Filling (NUSF)
- Input-Response Space-Filling (IRSF)

- **Robust Optimality-Based design**

* New in EY20

- Leverages capabilities in UQ
- Builds an empirical surrogate model
- Construct design using G-, I-, D- or A-optimality

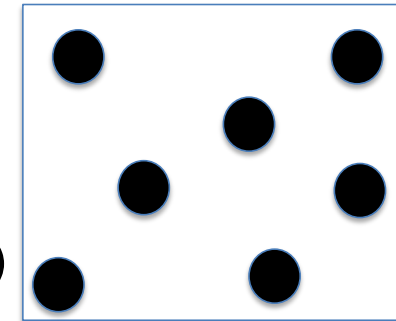
Focus: good prediction

Focus: good estimation of model parameters

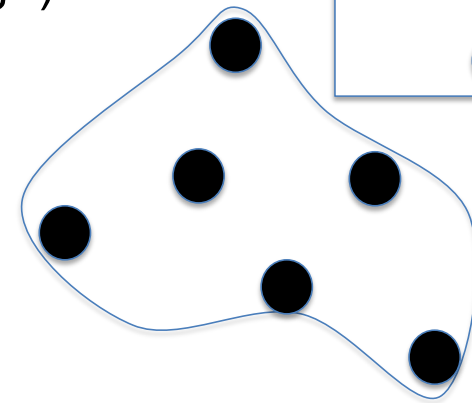
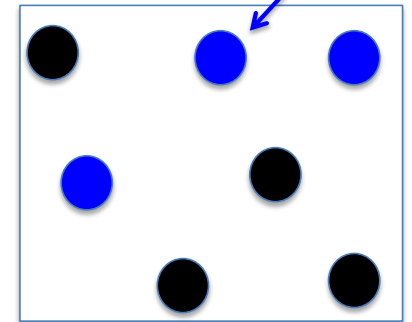


Uniform Space-Filling Designs

- Inputs:
 - Candidate set (specifies dimension of input space)
 - Previous data (optional)
 - Minimax or Maximin
 - Size(s) of designs
 - Number of random starts (time to generate design)
- Outputs
 - Multiple designs with criteria values



Previously
collected
data



Non-Uniform Space-Filling Designs

- Inputs:

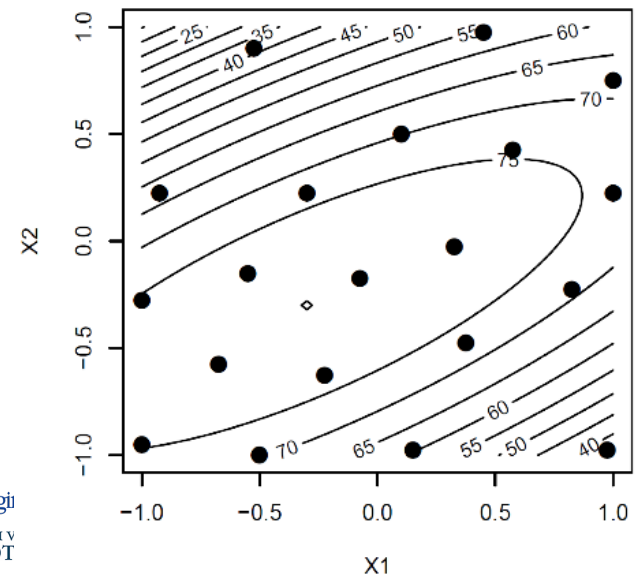
- Candidate set (specifies dimension of input space)
- Previous data (optional)
- Size of design
- MWR - Maximum Weight Ratio (degree of non-uniformity)
- Direct or Ranked scaling of weights
- Number of random starts (time to generate design)

Requires column for weights with value for each row

Flexible for different objectives

- Outputs

- Multiple designs with criteria values

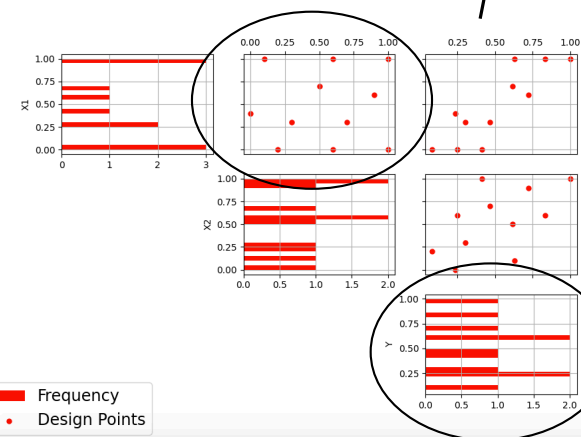
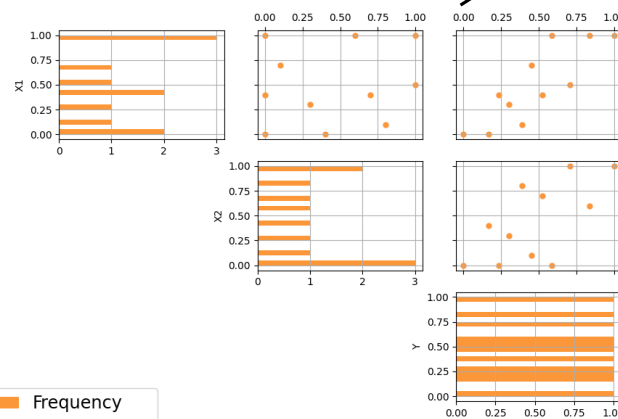
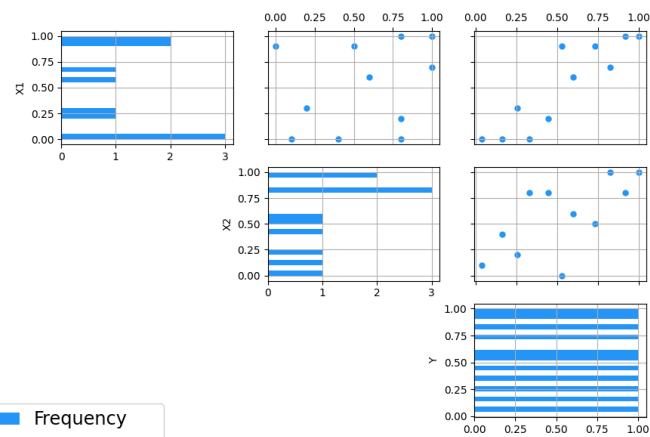
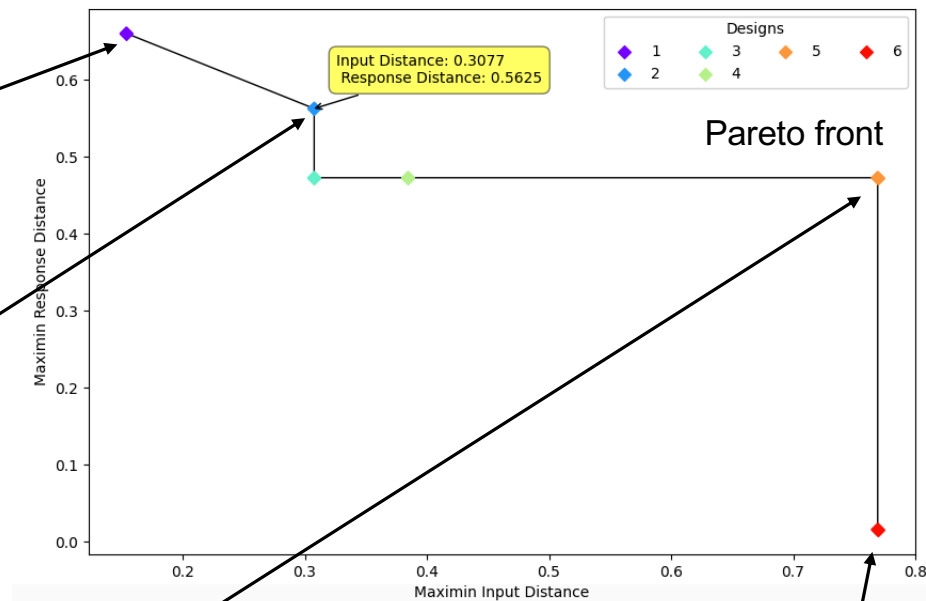
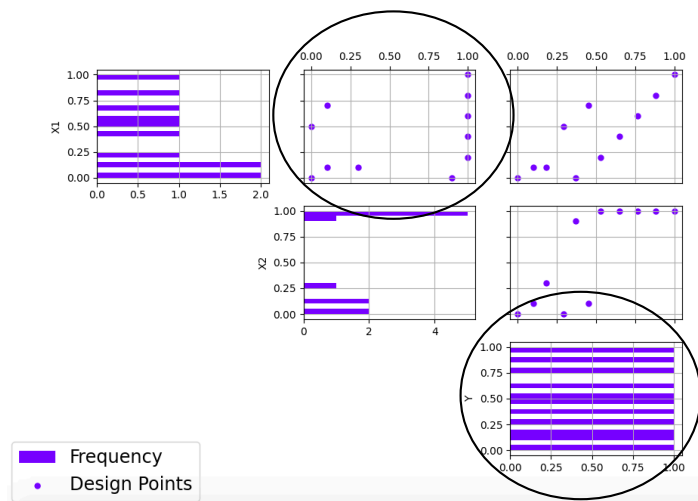


Input-Response Space-Filling Designs

- Inputs:
 - Candidate set (specifies dimension of input space)
 - Previous data (optional)
 - Minimax or Maximin
 - Size of design
 - Number of random starts (time to generate design)
- Outputs
 - Pareto front of objectively best designs to balance spacing in input and response spaces
 - Details for each design – which runs and criteria values

} Requires column for predicted response values





Robust Optimality-Based Design of Experiments (ODoE)

- **Goal:** construct ideal designs based on empirically fit models
- **Basic steps:**
 1. Select spreadsheet with columns of inputs and column(s) of responses
 2. Identify type of each input: Variable – not controllable during experiment
Design – controllable during experiment
 3. Specify details for each input (ranges, distribution shape, etc)
 4. Specify candidate set and evaluation set (optional)
 5. Fit an empirical model (different forms available) between inputs and response
 6. Evaluate fit of model. When satisfied with fit, proceed.
 7. Use model to generate a design. Choices:
 - Optimality criterion: G-, I- (focus: prediction),
D-, A- (focus: parameter estimation)
 - Design size
 - Number of Restarts



FOQUS -- [not saved yet]

Sequential Design of Experiments

Space-filling DoE (SDoE)

Robust optimality-based DoE (ODoE)

Design Setup

Generate New Candidate Set

Load Existing Set

Clone Selected

Delete Selected

Save Selected

File Type

Visualize

File Name

If you have a candidate set:

1. Press Load Existing Set and upload. Set File Type to Candidate.

2. If you also have previous data, press Load Existing Set and upload. Set File Type to Previous Data.

If you do not have a candidate set, press "Generate New Candidate Set"

When finished identifying previous data and candidate sets, press Continue.

Continue

Design Construction

	Descriptor	Visualize
Candidate File		
Previous Experiments/Data		
Output Directory		
Design Method		

Back to Selection

Open SDoE Dialog

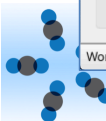
Select Variables (columns) and/or Sample Points (rows) for Deletion.
Type new values for outputs in the appropriate cells.

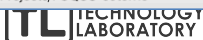
Filtering


Reset Table


Perform Deletion then Save as New Ensemble


Working Directory: /Users/sotorrio1/PycharmProjects/FOQUS-sotorrio


 Carbon Capture Simulation for Industry Impact


 TECHNOLOGY
LABORATORY


 BERKELEY LAB


 OAK RIDGE
National Laboratory


 LOS ALAMOS
NATIONAL LABORATORY
EST. 1943

 Northwest
NATIONAL
LABORATORY

 UNIVERSITY OF
NOTRE DAME

 TEXAS A&M
UNIVERSITY
AT AUSTIN





9

Load RS Train Data:

Optimality Criterion: ☒ G-Opt ☐ I-Opt ☐ D-Opt ☐ A-Opt

[illegible]Design Size: 1Number of Restarts: 3 ↕

Sequential Design of Experiments

- ☐ Space-filling DoE (SDoE)
- ☒ Robust optimality-based DoE (ODoE)

Load RS Train Data:

Browse...

Input Setup

	Input Name	Type	Fixed Value	PDF	PDF Param1	PDF Param2	Min	Max
1	X1	Variable	7339.5	Uniform			3004	11675
2	X2	Variable	1875	Uniform			1000	2750
3	X3	Design	0.15	Uniform			0.125	0.175
4	X4	Design	0.2	Uniform			0.1	0.3

Confirm Inputs

Design Setup

Do you have a candidate file? ☒ Yes

Load Existing Candidate Set

Do you have an evaluation file? ☐ Yes

Load Evaluation Set

☐ No

Generate New Candidate Set

☒ No

Candidate Set will be used as Evaluation Set

Select | File Name | Visualize

Select | File Name | Visualize

Delete Selection

Delete Selection

Confirm Design Setup

Output Setup

Select	Output Name	Response Surface	(cont'd)

Validate RS

Confirm RS

ODoE Setup

Optimality Criterion: ☒ G-Opt ☐ I-Opt ☐ D-Opt ☐ A-Opt

Design Size: 1

Number of Restarts: 3

Run ODoE

RS Predictions on Candidates (update with measurement uncertainty as needed)

Sequential Design of Experiments

☐ Space-filling DoE (SDoE)
 ☒ Robust optimality-based DoE (ODoE)

Load RS Train Data:

Input Setup

	Input Name	Type
1	X1	Variable
2	X2	Variable
3	X3	Design
4	X4	Design

Design Setup

Distributions

Sampling scheme

	Name	Type	Default	Min	Max	PDF	Param 1	Param 2
1	X1	Variable	7339.5	3004	11675	Uniform		
2	X2	Variable	1875	1000	2750	Uniform		

All Fixed

All Variable

Output Setup

Select

Output

ODoE Setup

Optimality Criterion: ☐

Do you have an evaluation file?

☐ Yes
 ☒ No

Candidate Set will be used as Evaluation Set

Number of Restarts:

Sequential Design of Experiments

☐ Space-filling DoE (SDoE)
 ☒ Robust optimality-based DoE (ODoE)

Load RS Train Data:

Input Setup

	Input Name	Type
1	X1	Variable
2	X2	Variable
3	X3	Design
4	X4	Design

Output Setup

Select | Output

ODoE Setup

Optimality Criterion: ☐

Simulation Ensemble Setup

Distributions

Sampling scheme

Show schemes:

☒ All
 ☐ For response surface analysis
 ☐ For adaptive response surface analysis

Monte Carlo

Quasi Monte Carlo

Latin Hypercube

Orthogonal Array

METIS

Full Factorial Design

of samples?

1000

Generate Samples

Done!

Cancel

Preview Samples

Done

FOQUS -- [not saved yet]

Session

Flowsheet

Uncertainty

Optimization

OUU

SDoE

Surrogates

Settings

Help

Sequential Design of Experiments

Space-filling DoE (SDoE)

Robust optimality-based DoE (ODoE)

Load RS Train Data:

/Users/sotorrio1/Desktop/odoe/ODoE_example.csv

Browse...

Input Setup

	Input Name	Type	Fixed Value	PDF	PDF Param1	PDF Param2	Min	Max
1	X1	Variable	7339.5	Uniform			3004	11675
2	X2	Variable	1875	Uniform			1000	2750
3	X3	Design	0.15	Uniform			0.125	0.175
4	X4	Design	0.2	Uniform			0.1	0.3

Confirm Inputs

Design Setup

Do you have a candidate file?

Yes

No

Load Existing Candidate Set

Generate New Candidate Set

Do you have an evaluation file?

Yes

No

Load Evaluation Set

Candidate Set will be used as Evaluation Set

Select	File Name	Visualize
1 <input checked="" type="checkbox"/>	ODoE_Candidate_1	<div>View</div>

Delete Selection

Select	File Name	Visualize
1 <input checked="" type="checkbox"/>	EvaluationSet.csv	<div>View</div>

Delete Selection

Confirm Design Setup

Output Setup

Select	Output Name	Response Surface	(cont'd)
1 <input checked="" type="checkbox"/>	Y1	MARS ->	MARS

Validate RS

Confirm RS

ODoE Setup

Optimality Criterion:

G-Opt

I-Opt

D-Opt

A-Opt

Design Size:

1

Number of Restarts:

3

Run ODoE

RS Predictions on Candidates (update with measurement uncertainty as needed)

Working Directory: /Users/sotorrio1/PycharmProjects/FOQUS-sotorrio

FOQUS -- [not saved yet]

Session

Flowsheet

Uncertainty

Optimization

OUU

SDoE

Surrogates

Settings

Help

Sequential Design of Experiments

Space-filling DoE (SDoE)

Robust optimality-based DoE (ODoE)

Load RS Train Data: /Users/sotorrio1/Desktop/odoe/ODoE_example.csv

Input Setup

	Input Name	Type	Fixed Value	PDF	PDF Param1	PDF Param2	Min	Max
1	X1	Variable	7339.5	Uniform			3004	11675
2	X2	Variable	1875	Uniform			1000	2750
3	X3	Design	0.15	Uniform			0.125	0.175
4	X4	Design	0.2	Uniform			0.1	0.3

Output Setup

Select	Output Name	Response Surface	(cont'd)
1 <input checked="" type="checkbox"/>	Y1	MARS ->	MARS

ODoE Setup

Optimality Criterion: ☒ G-Opt ☐ I-Opt ☐ D-Opt ☐ A-Opt

Model Validation of MARS Response Surface for Y1

Model Error Histogram

Actual vs. Predicted Data

Working Directory: /Users/sotorrio1/PycharmProjects/FOQUS-sotorrio



Sequential Design of Experiments

- ☐ Space-filling DoE (SDoE)
☒ Robust optimality-based DoE (ODoE)

Load RS Train Data: /Users/sotorrio1/Desktop/odoe/ODoE_example.csv

Browse...

Input Setup

Input Name	Type	Fixed Value	PDF	PDF Param1	PDF Param2	Min	Max
1 X1	Variable	7339.5	Uniform			3004	11675
2 X2	Variable	1875	Uniform			1000	2750
3 X3	Design	0.15	Uniform			0.125	0.175
4 X4	Design	0.2	Uniform			0.1	0.3

Confirm Inputs

Design Setup

Do you have a candidate file? ☐ YesLoad Existing
Candidate SetDo you have an evaluation file? ☒ YesLoad
Evaluation Set☒ NoGenerate New
Candidate Set☐ NoCandidate Set will
be used as
Evaluation Set

Select	File Name	Visualize
1 <input checked="" type="checkbox"/>	ODoE_Candidate_1	View

Delete Selection

Confirm Design Setup

Select	File Name	Visualize
1 <input checked="" type="checkbox"/>	EvaluationSet.csv	View

Delete Selection

Output Setup

Select	Output Name	Response Surface	(cont'd)
1 <input checked="" type="checkbox"/>	Y1	MARS ->	MARS

Validate RS

Confirm RS

RS Predictions on Candidates (update with measurement uncertainty as needed)

	X3	X4	Y1 mean	Y1 std
1	0.153070	0.151790	6.404750	1.962490
2	0.149290	0.281340	7.045540	2.170210
3	0.153740	0.224880	6.537670	1.888260

ODoE Setup

Optimality Criterion: ☒ G-Opt ☐ I-Opt ☐ D-Opt ☐ A-Opt

Design Size: 1

Number of Restarts: 3

Run ODoE



Sequential Design of Experiments

- ☐ Space-filling DoE (SDoE)
☒ Robust optimality-based DoE (ODoE)

Load RS Train Data: /Users/sotorrio1/Desktop/odoe/ODoE_example.csv

Browse...

Input Setup

Input Name	Type	Fixed Value	PDF	PDF Param1	PDF Param2	Min	Max
1 X1	Variable	7339.5	Uniform			3004	11675
2 X2	Variable	1875	Uniform			1000	2750
3 X3	Design	0.15	Uniform			0.125	0.175
4 X4	Design	0.2	Uniform			0.1	0.3

Confirm Inputs

Output Setup

Select	Output Name	Response Surface	(cont'd)
1 <input checked="" type="checkbox"/>	Y1	MARS ->	MARS

Validate RS

Confirm RS

ODoE Setup

Optimality Criterion: ☒ G-Opt ☐ I-Opt ☐ D-Opt ☐ A-Opt

Design Size: 1

Number of Restarts: 3

Design Setup

Do you have a candidate file? ☐ Yes

Load Existing Candidate Set

☒ No

Generate New Candidate Set

Do you have an evaluation file? ☒ Yes

Load Evaluation Set

☐ No

Candidate Set will be used as Evaluation Set

Select	File Name	Visualize
1 <input checked="" type="checkbox"/>	ODoE_Candidate_1	View

Delete Selection

Confirm D

Select	File Name	Visualize
1 <input checked="" type="checkbox"/>	EvaluationSet.csv	View

RS Predictions on Candidates (update with measurement uncertainty as needed)

	X3	X4	Y1 mean	Y1 std
1	0.153070	0.151790	6.404750	1.962490
2	0.149290	0.281340	7.045540	2.170210
3	0.153740	0.224880	6.537670	1.888260

===== ODoE RESULTS =====

Results for Run #1:
Best Design(s): [16, 15]
Best G-Optimality Value: 1.814570

Results for Run #2:
Best Design(s): [15, 5]
Best G-Optimality Value: 2.133548

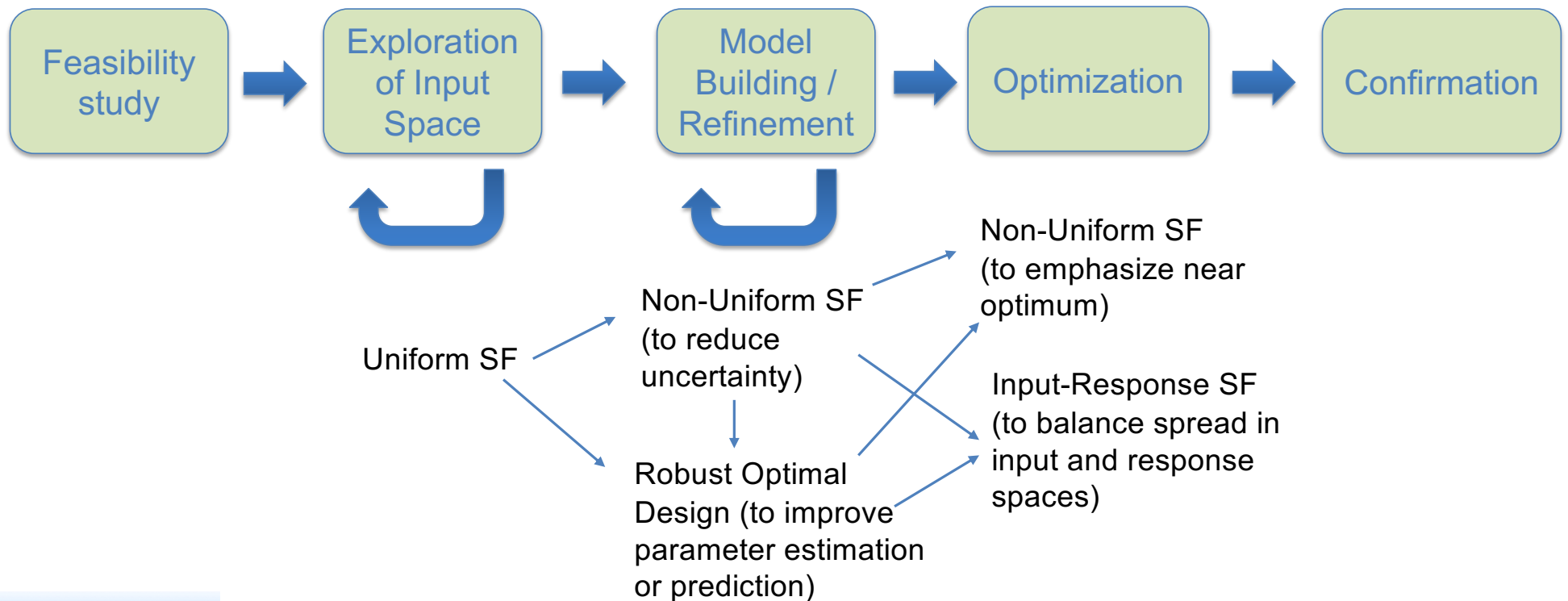
Results for Run #3:
Best Design(s): [15, 5]
Best G-Optimality Value: 1.781109

OK

How this work fits into CCSI²

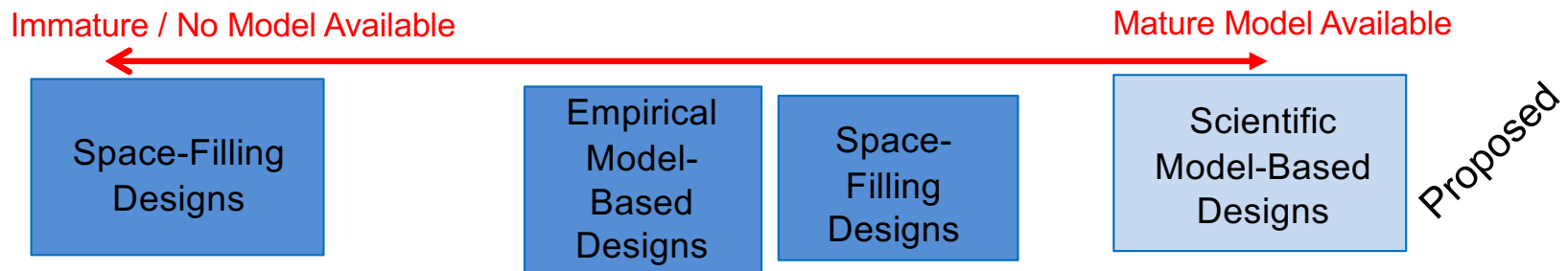
Computer Experiments

Physical Experiments – lab, pilot



Future R&D Plan and Challenges

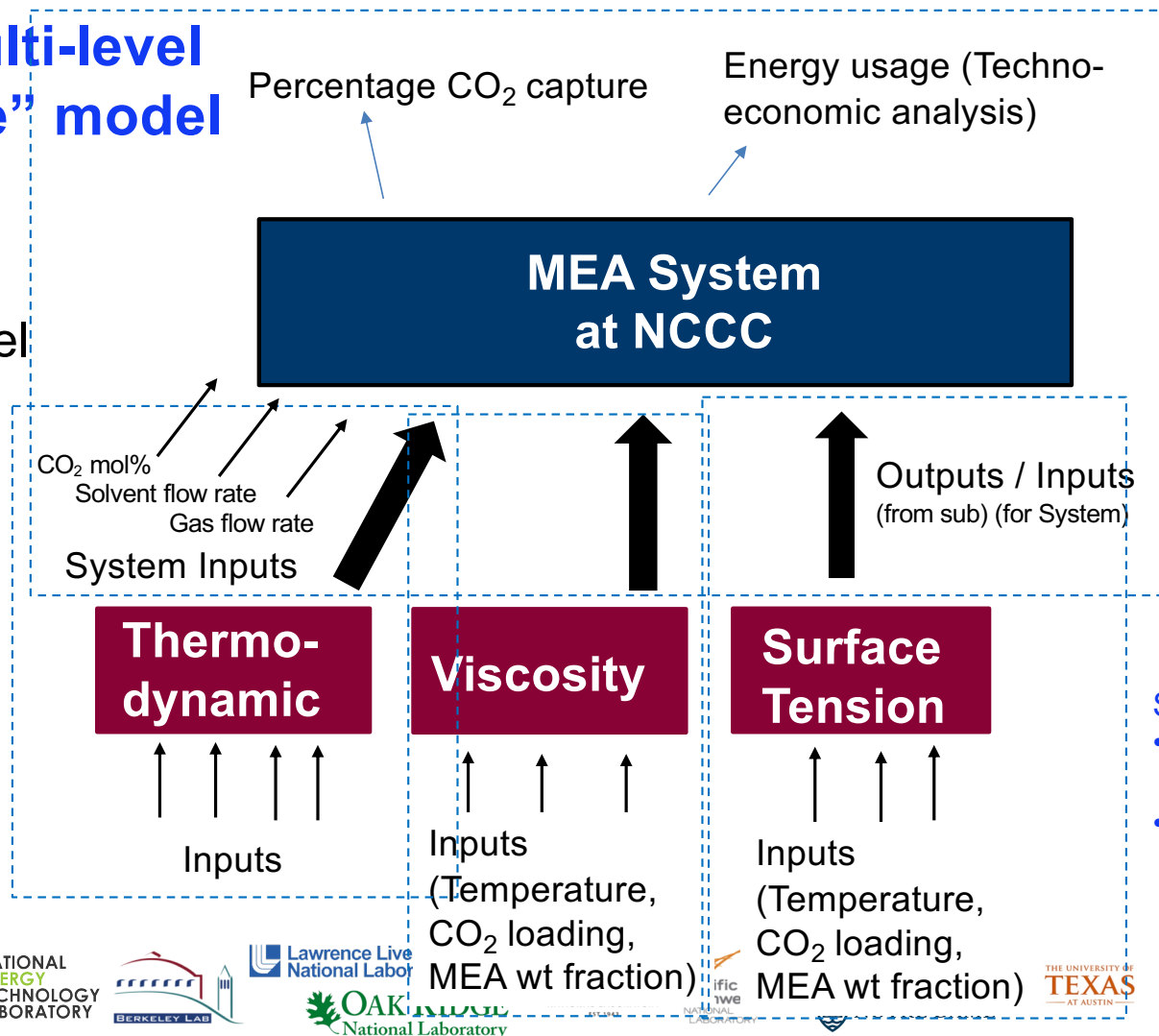
- There are still **big strategic opportunities** to pursue:
 1. Our current tools focus on the individual experiment level, but there are powerful opportunities when we **consider the big picture**
 - CCSI² supports development of systems and models spanning basic science to deployment. This involves science sub-system models, overall system model – each with their own associated costs and utility
 - When we consider multiple different experiments to achieve strategic goals for system performance, consider
 - what types of data should we be collecting?
 - how much of each type?
 - what design within each type?
 2. The CCSI² approach is **model-centric**. Additional design of experiments tools can leverage knowledge from a mature mathematical / science model



Design for multi-level “conglomerate” model

Engineering model
of pilot system

Fundamental
science models



Overall goal:
- Best prediction throughout the input space of NCCC system model

4 “experiments” to collect data, each with different

- Costs
- Inputs / outputs
- Utility

Scenarios to explore:

- Different levels of maturity of model
- Different available data



New Capability: Science Model-Based Design of Experiments

Main Idea: use full model equations directly to optimizing experimental campaigns to improve parameter estimates

- + Avoids need to build/validate surrogates
- + Discriminate between alternative mechanistic models
- Requires access to equations (e.g., Pyomo)

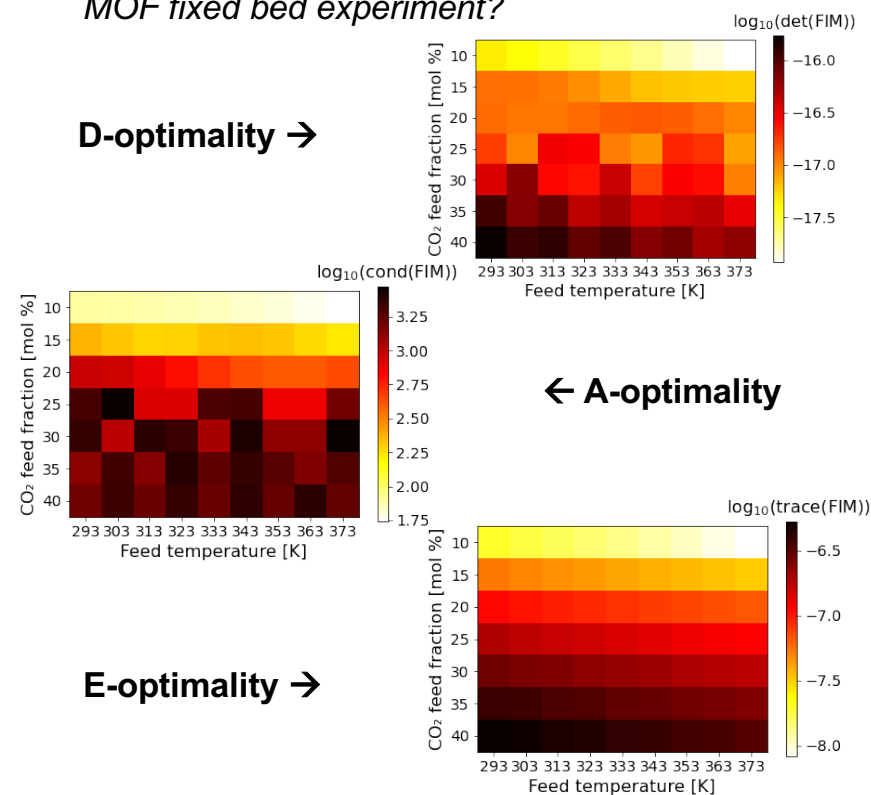
EY 2021 Progress (Sub-Task 2.1 & 3.1)

- Created MBDOE framework that works with any Pyomo model
- Demonstrated capability in DoE case study for fixed-bed MOF characterization

EY 2022 Proposed Work (Sub-Task 3.1)

- Release framework open source as Pyomo package
- Create plan to integrate MBDOE in FOQUS
- Algorithm improvements to increase speed & robustness

Example: What is the optimal CO₂ feed composition and feed temperature for next MOF fixed bed experiment?



Planned work for EY21-EY23

- EY21
 - Missing values / Imputation for NUSF and IRSF (LLNL)
 - Videos and Documentation update for all capabilities (LANL & LLNL)
 - Robust optimality-based DoE enhancement (LLNL)
 - Science-based optimal design methodology development (ND)
 - Design for Conglomerate model methodology development and demonstration (LANL)
 - Collaboration with Pilot project teams – write up case study (LANL)
- EY22
 - Integration of Science-based optimal design into toolset
 - Integration of Design for Conglomerate model into toolset
 - Collaboration with Pilot project teams – write up case study
 - Update supporting materials (video, documentation)
- EY23
 - Collaboration with Pilot project teams – write up case study



Proposed for Breakout Discussion

- **Breakout Discussion**

- Design for Multi-level “conglomerate” models
- Design capability for Science-based models
- Description of planned supporting materials – documentation, videos
- Where do we anticipate design of experiments support being needed in the coming years?
 - Pilot studies: RTI, MTR, TDA
 - DOCCSS: PNNL CO2BOL, LBNL MOF
 - Other?
- Wishlist for other design capabilities

- **Open Q&A**

- ??



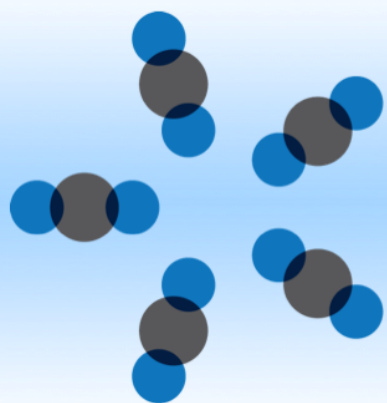
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Charles Tong (LLNL)





CCSI²

Carbon Capture Simulation for Industry Impact

For more information

<https://www.acceleratecarboncapture.org/>

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